Mihály Fazekas [1], *Jiri Skuhrovec* [2], *Johannes Wachs* [3]

Corruption, government turnover, and public contracting market structure

Insights using network analysis and objective corruption proxies

Working Paper series: GTI-WP/2017:02

Version 1.0

September 2017, Budapest, Hungary

[1] University of Cambridge and Government Transparency Institute, corresponding author: mf436@cam.ac.uk
[2] Charles University and Datlab
[3] Center for Network Science, Central European University and Government Transparency Institute

Abstract

Many policymakers and researchers study and debate how to control and limit corruption. Few have examined the mechanisms by which corruption distorts markets and how they may be influenced to mitigate negative effects. To develop this new perspective, we study how corruption effects the structure of public contracting markets modelled as networks of connected buyers and suppliers. We examine the impact of political power-sharing on these networks via government turnover timing and frequency. We do so in two similarly corrupt countries with different electoral systems, the Czech Republic and Hungary. Measuring corruption at the contract-level using a composite index of corruption red flags, we find that high corruption risk public buyers have sparser local neighbourhoods, meaning that they contract with fewer suppliers than expected. A buyer with an additional corruption red flag on average has 10% fewer suppliers. Moreover, highly corrupt buyers change their networks 21-38% more extensively across years with government turnover, revealing how corruption distorts markets. The effects are larger and more abrupt in Hungary than in the Czech Republic, suggesting that the frequency of electoral contestation mitigates the negative economic impact of corruption.

JEL Codes: Market Structure, Pricing, and Design - D40, Microeconomic Policy: Formulation, Implementation, and Evaluation - D04, General Public Economics - H0

Keywords: public procurement; corruption; indicators; network; government change

Acknowledgements: The authors would like to thank the following colleagues for helpful discussion and feedback: Zsofia Czeman, Andras Borsos, Balazs Vedres, David Deritei, Bence Toth, Carl Nordlund, and Silvia Fierascu.

1. Introduction

Evidence that corruption is detrimental to human well-being and economic growth is robust both in high and low income countries (Hessami, 2014). Corruption is thought to be especially wide spread in public procurement, owing to the large sums of money involved, the complexity of contracts, and the discretion given to officials (Baldi, Bottasso, Conti, & Piccardo, 2016; OECD, 2007, 2015). Even though early works on corruption recognized its importance, empirical work has too often neglected that its social cost can vary substantially depending on its “industrial organization” (Shleifer & Vishny, 1993), in other words the same level of corruption may imply different corruption costs (Blackburn & Forgues-Puccio, 2009). For example, if firms compete on cost including bribes, the positive impact of competition on productivity would remain. If firms are excluded from the market and corrupt firms do not need to compete at all, social costs will compound over time, leading to a gross misallocation of resources (Aidt, 2016).

Recent developments in economics and political science have led to new definitions of corruption, especially elite-driven systemic forms of it, in terms of favouritism and exclusion of groups in the allocation of public resources (North, Wallis, & Weingast, 2009). This theoretical development represents a major departure from understanding corruption merely as a transactional tax paid at the point of contact (i.e. bribery) and raises fundamental questions about the impacts of corruption in terms of market structure and dynamics.

While there is an extensive academic literature on the macro impacts of corruption on issues such as budget composition (Mauro, 1998), military spending (Gupta et al. 2001), technological complexity, etc.(Hessami, 2014), there is relatively little evidence to date on the impact of micro-level mechanisms on the market (Beekman, Bulte, & Nillesen, 2013; Olken, 2007). We suggest that the relational nature of public procurement data, consisting of buyers and suppliers, make it a prime candidate for study using the tools of network analysis. Indeed recent advances in the economics of networks on topics as diverse as job search, R&D collaboration among firms, and cooperative games (Goyal, 2012; Jackson, 2010) indicate the potential value of network approaches to economic questions. Few studies look at how corruption leads to favouring connected actors while excluding others despite the fact that exclusion has become a key definition and marker of corruption (Diwan, Keefer, & Schiffbauer, 2016; Freund, Nucifora, & Rijkers, 2014; Goldman, Rocholl, & So, 2013). Crucially, relevant studies only look at the existence of personal connections and their impacts (Goldman et al., 2013) rather than directly studying the relations themselves and the forms, degrees, and evolution of corrupt exclusionary relationships.

The article has two objectives: it studies the impact of corruption on the structure of government contracting markets viewed as networks and how government turnover helps control corrupt market distortions hence its social costs. This requires, first that we distinguish corrupt and non-corrupt contracting relationships using proxies capturing high risk situations such as non-advertised tender attracting only one bidder on a competitive market or convoluted tender specifications seemingly tailored to one company. Second, the amount of openness and clustering in public buyers’ local contracting neighbourhood is predicted by such corruption risks. Third, we turn to the impact of government change on these network neighbourhoods and the relationship between corruption risks and network structure. We seek to demonstrate that the same prevalence of corruption can lead to different corrupt network formations and hence impose different social costs, both of which are very much influenced by actor expectations and time horizons determined by electoral contestation. If our findings are correct, they open ways of controlling the harmful effects of corruption even if its prevalence remains unchanged.

We study these questions in the context of public procurement spending in the Czech Republic in 2006-2013 and Hungary in 2009-2014. Public procurement is an area of government activity with a particularly high prevalence of corruption, favouritism, and rent-seeking both globally and in Central and Eastern Europe (CEE) (OECD, 2007). These two CEE countries provide a good contrast given their very similar levels of development, regulatory framework, prevalence of corruption, but contrasting electoral systems and government turnover trajectories. The public procurement regulatory and administrative systems are similar due to the overarching EU framework. Prior cross-country research on corruption and state capture generally grouped the two countries together, for example as c*ompetitive clientelistic regimes* (Fazekas & Tóth, 2016; Mungiu-Pippidi, 2015). Crucially for our research design, the Hungarian electoral system allows for and encourages strong majorities, in some cases leading to landslide government turnover. For example, national and local elections are only a few months apart and first-past-the-post electoral rule plays a dominant role. The Czech system, with staggered local and central elections and more proportional representation, rarely leads to strong majorities. We can argue that the differences in electoral systems between the two countries and the corresponding different political incentives they create are exogenous to the corruption risk-contracting network structure relationship we investigate. Hence, cross-country differences in the effect of corruption on network structure can be attributed to differences in electoral competition in the presence of adequate controls.

Our contributions are as follows: First, we develop novel indicators objectively proxying corruption in government tenders using widely available administrative data. Our datasets and a range of other similar databases are available at http://digiwhist.eu/resources/data/. Second, we develop network science methods to directly operationalise emerging concepts of corruption, understood as limited access to public resources, on the level of buyers and suppliers and contracting relationships between them. As these methods make use of the same widely available public contracting data as our corruption risk indicators, the potential for replicability is considerable. Our methods also have substantial policy applications offering insights for audit bodies and regulators on where corruption risks are highest. Third, we provide a quantitative test of theories of how corruption distorts market structure in public contracting networks which we suggest is novel. Fourth, we precisely test generic theories of how government turnover mitigates the market distorting impacts of corruption, providing empirical evidence for the long-standing claim that the industrial organization of corruption fundamentally influences its costs.

We find that high corruption risk buyers have significantly sparser local neighbourhoods. We quantify this using a network science measure which we call *competitive clustering*, which measures the extent to which a buyer diversifies its contract awards in its network neighbourhood. Our results show that buyers are less likely to enter contracting relationships with suppliers nearby in the network and are more likely to award contracts to fewer suppliers. This supports the hypothesis that corruption is about exclusion. Moreover, buyers with both high corruption risk and sparse neighbourhoods, which we refer to as *captured*, are significantly less stable around changes of government, supporting the theory that the political cycle shapes these markets. The effect sizes of both the relationship between corruption risk and competitive clustering and the instability of captured buyers across years with a change in government are larger in Hungary than in the Czech Republic. We claim that this implies that market distorting impact of partisan favouritism is lower in the Czech Republic than in Hungary. We attribute this to the higher frequency of political turnover and more heterogeneous power-sharing in the Czech Republic across the timeframe of our data.

The rest of the paper is organized as follows. Section 2 discusses theories of corruption and how they apply to public procurement markets. Section 3 describes the data and network science concepts used. Section 4 defines the key independent and dependent variables, including corruption risk proxies and network attributes of buyers. Section 5 describes our models and identification strategy. Section 6 presents the results and Section 7 concludes.

2. Theory

Much of the earlier scholarship on corruption has predominantly understood it as bribery, as a type of informal tax on economic transactions when companies interact with bureaucrats (Diaby & Sylwester, 2014; Hanousek & Kochanova, 2016; Knack, Biletska, & Kacker, 2017). While this perspective on corruption certainly has its merits, it is less applicable to contexts of high-level corruption conducted by elites in a systemic and institutionalised fashion (Rose-Ackerman, 2015). Moreover, there is an emerging literature in economics and political science which defines corruption in terms of access to power and public resources and the impartiality of exercising public authority (Mungiu-Pippidi, 2015; North et al., 2009; Rothstein & Teorell, 2008). We build on this strand of the literature as it fits the context of public procurement corruption particularly well. Specifically we define corruption in public procurement as the allocation and performance of government contracts in violation of prior explicit rules and principles of open and fair public procurement in order to benefit a closed network while denying access to all others (Fazekas, Tóth, & King, 2016). Such complex corruption transactions are driven by coalitions of various sizes and with different structures. These adapt to changing regulatory and oversight conditions while continuing to extract rents (Hudon & Garzón, 2016).

We draw on theory understanding competitive clientelistic regimes as a sub-type of limited access orders which determines the type and prevalence of corruption throughout society (Mungiu-Pippidi, 2015). In competitive clientelistic regimes such as the Czech Republic and Hungary, elections and government turnover are regular, but whoever takes control of the state uses it for corrupt rent extraction. The group in control benefits its favoured private enterprises through government contracts, and also regulation, privatisation, access to state-backed loans, etc.. This creates a specific partisan form of corruption by which elite groups compete for political and economic control and use it to enrich their closed circles by favouring those suppliers which contributed to their electoral campaigns or directly pay ‘kickbacks’ to political office-holders (Dávid-Barrett & Fazekas, 2016). Even though corruption is widespread in such countries, there is a strong variation in the level of corruption within them (e.g. regionally or sectorally) and normally some islands of impartial values and low corruption exist (Charron, Dijkstra, & Lapuente, 2015). Such a setting fundamentally influences elite time horizons and the incentives to expropriate rents with corruption increasing in the likelihood of losing office (Wright, 2008).

Understanding corruption in competitive clientelistic regimes as predominantly exclusion at the actor level, that is reflecting the power of the captor group able to dominate public procurement in any public buyer organisation, gives rise to novel predictions hitherto under-explored in the literature both theoretically and empirically. Corruption is in effect a powerful market organising force which determines contractual relationships, their distribution and which actors have access to them. A dominant corrupt coalition in public procurement will tilt market forces to increase the market share of companies linked to the coalition potentially up to the point that only favored companies are winning contracts while non-favored suppliers never win. In other words, when compared to a corruption-free market structure, corrupt markets are expected to be imbalanced to the benefit of suppliers connected politically to corrupt public officials. The degree to which this imbalance deviates from the corruption free benchmark depends on the strengths of public corruption controls such as audit institutions or courts (Dávid-Barrett & Fazekas, 2016) and also the degree of partisanship in the private economy (Stark & Vedres, 2012). Any degree of such imbalances is damaging to the economy as unfair treatment or outright exclusion of some suppliers from public tenders harms economic efficiency through weakening competition, and incentives to deliver on contract (Coviello & Mariniello, 2014; Lewis-Faupel, Neggers, Olken, & Pande, 2016). Understanding corruption as an organising force in public procurement markets at the level of public buyers with varying degrees of bias, we put forward two hypotheses:

H1: Higher corruption leads to uneven distribution of spending among suppliers on the market.

H2: Higher corruption leads to stronger exclusion of non-favored suppliers.

The theory of competitive clientelistic or particularistic regimes also suggests when the distribution of power changes, for example during a change in government, the fortunes of favoured suppliers should change much more than that of their less-favoured rivals. Their success was dependent on whoever holds political power and so a change in the distribution of political power should be reflected in changes in the market (Goldman et al., 2013; Mungiu-Pippidi, 2015). If government accountability is effectively pursued through elections then we should expect government turnover weakening the effects of corruption on network structure, that is genuinely increasing market openness (Eggers, 2014; Larcinese & Sircar, 2017). However, if electoral accountability is ineffective, government change would only replace the captors but leave the essentially biased structure of procurement markets unaltered (Fazekas & Tóth, 2016). Given the high degree of partisanship in Hungary and also to a lesser degree in the Czech Republic, we hypothesize that:

H3: Government turnover temporarily mutes the effect of corruption on the exclusion of non-favored suppliers (competitive clustering).

The political economy literature has gathered great deal of evidence on the effects of electoral contestation on corruption without a clear-cut conclusion (Broms, Dahlström, & Fazekas, 2017; Coviello & Gagliarducci, 2017). However, a hitherto unexplored effect of electoral accountability may not be the diminishing amount of corruption rather curbing its harmful effects. While any single election or government change will not alter the effect of corruption on market structure and dynamics for long, the frequency, competitiveness, fragmentation of elections may have a profound effect on the entrenchment of corrupt relationships. Frequent elections with uncertain outcomes may compel corrupt elites to pursue predatory strategies in the absence of programmatic and institutionalised parties; however, in the presence of a well-established party system - characteristic of both the Czech Republic and Hungary - regular electoral uncertainty may motivate corrupt elites to exercise restraint, smooth rent extraction over electoral terms, and also invest into long term policies increasing the pool of extractable rents (Broms et al., 2017). This is due to two main reasons. One the one hand, we suggest that this is because it takes a long time to gain control over rent extraction in public procurement, which requires the coordination of bidding suppliers, bureaucratic positions (e.g. procurement administrators), key political offices (e.g. procurement project allocation), and oversight bodies (e.g. arbitration boards). On the other hand, politicians will seek to minimize the risk of retrospective investigations into corrupt deals by the subsequent government once office is lost. A fragmented electoral system where multiple elections are held for different public offices on the local, regional, and national levels (the Czech Republic has separate elections for the two chambers of national parliament and the president), may pose further constraints where political power is more diffused and different political groups dynamically have to bargain over rent sharing and potentially keeping each other in check (Blackburn & Forgues-Puccio, 2009; Neto et al., 2015). Hence, we hypothesize that

H4: political power sharing driven by frequent electoral contests weakens the effect of corruption on market structure.

3. Data, indicators, and identification

3.1 Data used

The government contracting data studied in this paper were collected from the official government public procurement portals using automated web scrapers and parsing algorithms extracting key fields from semi-structured html code (for technical database building details see Czibik, Tóth, & Fazekas, 2015). All contracts regulated by national public procurement laws must be reported on these portals, if their value is above official thresholds documented in Table 1. Besides contracts below thresholds, certain contracts may be missing such as top secret defense contracts. By implication, our contracting data provide a close to complete picture of what governments, state owned enterprises, and semi-public bodies financed by the state buy to the value of 3-7% of annual GDP. They are also very diverse, encompassing contracts in markets such as office supplies, specialized legal services, road construction, or electricity. We collected all contracts in Hungary from 2009 to 2014, and in the Czech Republic from 2006 to 2013. The time series are partially non-overlapping and do not extend to the present because of changes in reporting formats. These sets comprise the maximally comparable contract-level databases available for these two countries.

TABLE 1: PRIMARY SOURCES OF PUBLIC PROCUREMENT DATA AND MINIMUM THRESHOLDS

Country	Data Source	URL	Threshold (EUR)
Czech Republic	Ministerstvo pro místní rozvoj ČR	http://www.isvzus.cz/usisvz/	39,000
Hungary	Közbeszerzési Értesítő	http://www.kozbeszerzes.hu/	27,300

From each contract we extract the buyer (also referred to in the literature as the issuer of the contract) and supplier (a.k.a the firm), the number of bids submitted, the date of award, the contract value (which we transform to Euros and adjust for inflation) (Table 2), and several further buyer, supplier, and contract-level variables used for calculating the Corruption Risk Index (CRI) (for brief definition see below, full details in (Fazekas, Chvalkovská, Skuhrovec, Tóth, & King, 2014)).

TABLE 2: SUMMARY STATISTICS

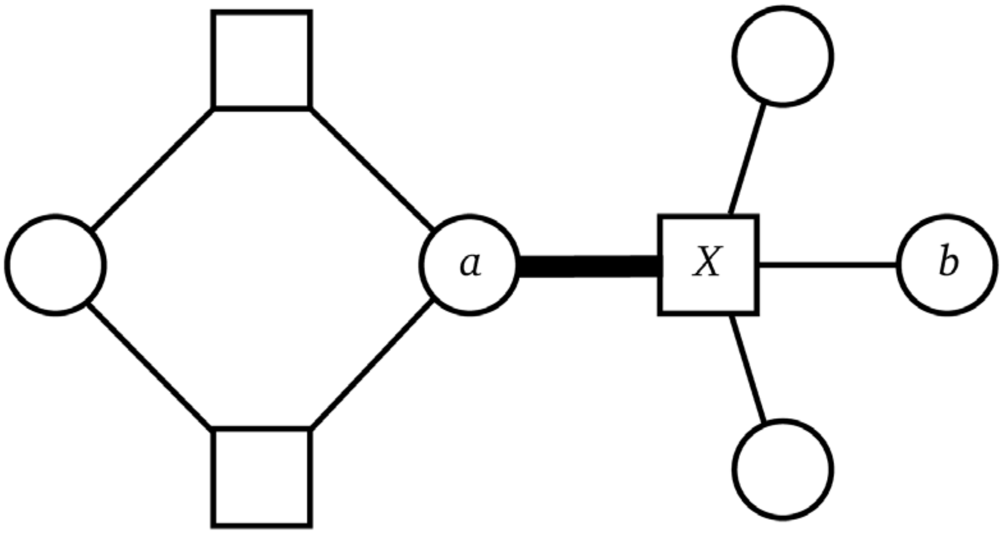
	Number of Contracts	Unique suppliers	Unique buyers	Total Contract Value (EUR)	Mean Contract Value	Std. Dev. Contract Value	Mean CRI	Std. Dev. CRI	Share Single Bidder
Czech Republic	92,511	13,178	6,892	71,154,784,414	769,149	7,044,414	0.288	0.168	0.246
Hungary	73,883	17,084	3,106	11,733,786,615	158,816	1,888,193	0.315	0.205	0.307

3.2 Government Contracting Markets as Networks

Networks have been used to study a wide variety of phenomena from the natural and social sciences (Borgatti et al., 2009, Schweitzer et al., 2009, Albert & Barabási, 2002). We represent public procurement markets as bipartite networks. When a buyer and a supplier have a contracting relationship, we connect them by an edge. The edge carries the total contract value, the count of contracts, and the average corruption risk of contracts between the buyer and supplier. Bipartite networks refer to networks with two distinct classes of nodes (in our cases buyers and suppliers) among which there can be no edges[1]. We visualize a toy example network in Figure 1.

[1] In some rare cases buyers (public companies) serve as suppliers for other buyers. We consider each such entity twice: as a buyer and a supplier, as though they were distinct.

FIGURE 1: A NETWORK REPRESENTATION OF AN ARTIFICIAL TOY PUBLIC CONTRACTING MARKET.



Note: The squares represent buyers and the circles suppliers. A buyer and supplier are connected by an edge if they have a contracting relationship. The width of the edge increases as the value of the contracts between the buyer and supplier increases. For example, suppliers ‘a’ and ‘b’ are both connected to buyer X, indicating that they have won at least one contract from X. Supplier a has won substantially more contract value from buyer X, indicated by the thickness of the edge connecting the two.

Such networks have been used to study a variety of markets in which actors can be split into two groups (Rausch & Casella 2001, Kirman 2010). These market networks have some similarities to social networks that are increasingly of interest to economists (Jackson et al., 2017). Those networks are used to study contagion, externalities, and cooperative games (among other topics). As market networks are defined by transitions between entities and not relationships between individuals, we are careful to adopt and relate to the social networks literature.

In the case of public contracting, this approach is relatively new. Fazekas and Tóth (2016) established that high corruption risk organizations are clustered in Hungarian procurement markets viewed as networks indicating the presence of state capture, and that global network measures of the market reflect centralizing trends in the bureaucracy. Fierascu (2017) expands on this approach and relates local network configurations to corruption risk across several years of Hungarian procurement. This perspective is perhaps closest to our own, as we also seek to relate local network information with corruption, but rather than enumerating configurations globally, we will study each buyer’s local neighbourhood.

In Figure 2 we visualize the 2009 Czech and Hungarian public procurement markets as networks. We show only the nodes and edges connected to the largest component of the graph. The disconnected nodes are less than 10% of the network in both cases. We note that even though we consider the entire market, including contracts for hospital beds, road repair, and school lunches, the networks are quite dense and well-connected. Indeed the average path length, meaning the average number of steps it takes to get from one randomly chosen node to another is only six. This suggests that classifying contracts by location or industry will invariably create some artificial distinctions. Indeed in our models we always analyse the whole market with sector-level dummies, rather than creating separate models for each sector.

FIGURE 2: HUNGARIAN AND CZECH PROCUREMENT MARKETS IN 2009.

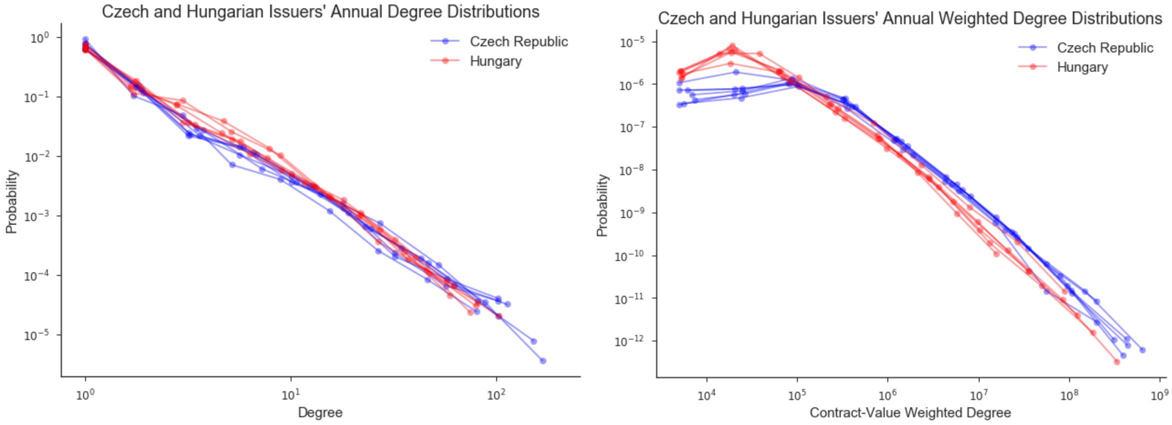
Note: Green nodes are buyers, purple nodes are suppliers. Edges are colored red if the average CRI of contracts between the buyer and supplier in question are at least one standard deviation above the market average.

3.3 Network Summary statistics

Empirical economic and social networks exhibit regularities that distinguish them from random networks. We have already referred to the high proportion of nodes in the largest connected component and to the short average distance between nodes. Another such regularity is the heterogeneity of the degree distribution. The degree of a node is defined as the number of neighbours of a node. The weighted degree of a node is the sum of the edge weights adjacent to that node. For example, if buyer A contracts with suppliers X and Y, with values of 500,000 Euro and 100,000 Euro, respectively, we say that buyer A has degree 2 and weighted degree 600,000.

In Figure 3 we plot the log-binned unweighted and weighted degree distributions of buyers in Hungary and the Czech Republic across all the years in our data on a log-log scale. We see that in all markets buyers have highly heterogeneous distributions: there are hub buyers which award many contracts and peripheral buyers with much fewer suppliers. In other words, the distribution of contracting across institutions is far from normal. In both the weighted and unweighted cases we see remarkable consistency over the years within the countries. As the distributions are stable over time, we suggest that any regulatory change in the procurement process, or changes in the distribution of procurement responsibilities of entities are small. Hence the data are comparable year to year. A significant change in the slope of either line would indicate a true change in the system of contract awards.

FIGURE 3: ANNUAL UNWEIGHTED AND WEIGHTED DEGREE DISTRIBUTIONS FOR BUYERS IN HUNGARY AND CZECH REPUBLIC.



Note: Observations are log-binned and the axes are on a log-log scale. The consistency of the distributions suggests that there was no impactful change of the system governing contract issuance.

4. Indicators

4.1 Measuring corruption risks objectively: the main independent variable

Micro-level objective indicators of corruption in public contracting are a recent development (Fazekas et al., 2016). The online reporting of public procurement contracts in several countries makes it possible to score contracts for corruption risk en masse. We use an established method of measuring corruption risk called the *Corruption Risk Index* (hence CRI), which checks for certain red flags in contract metadata known from case studies to be linked to corruption (OECD, 2007; Pricewaterhouse Coopers, 2013; World Bank, 2009). The CRI is an aggregate measure counting the presence of these red flags as measured by elementary corruption risk indicators (Fazekas & Kocsis, 2017).

The elementary corruption risk indicators fall into three groups: those describing red flags in the submission phase of the tendering procedure, the assessment of bids phase, and the outcome phase (Table 3). Elementary indicators that examine the submission phase measure the extent to which a procedure restricted participation. Companies may be discouraged or blocked from fair participation if the call for tenders was not published in the official journal, if the call was modified during the submission period, if the procedure type was not open, if the eligibility criteria were over-determined (proxied by the character length of the criteria relative to industry average), or if the period from call to deadline was short. Non-favored companies may still be barred from winning a tender in the assessment phase. Non-price or quantity criteria in the evaluation of bids give the decision-maker discretion and limits accountability. If the time it takes the buyer of the tender to decide on the winner is very short, it may indicate that a premediated choice was made. Finally, a single bidder outcome in a competitive market is a strong indicator that the tender lacked competition where competitive markets are defined by product group-location combinations with at least 3 different suppliers to the government over the whole period (this restriction only marginally shrinks the analyzed sample).

TABLE 3: CONTRACT-LEVEL INDICATORS OF CORRUPTION RISK.

Proc. phase	Indicator name	Indicator values
submission	Call for tenders publication	0=call for tender published in official journal 1=NO call for tender published in official journal
	Call for tender modification	0=NOT modified call for tenders 1=modified call for tenders
	Procedure type	0=open procedure 1=non-open procedure (e.g. invitation tender)
	Length of eligibility criteria	Number of characters relative to market average
	Length of advertisement period	Number of days between the publication of call for tenders and the submission deadline (for short submission periods weekends are deducted)
assessment	Weight of non-quantitative evaluation criteria	Sum of weights for evaluation criteria which are NOT related to prices or quantities
	Length of decision period	number of days between submission deadline and announcing contract award
outcome	Single bidder contract (valid/received)	0=more than 1 bid received 1=1 bid received

The composite *Corruption Risk Index* (CRI) is the arithmetic average of the scaled elementary indicators, all falling in the 0-1 range. By tracking a composite index of indicators, the measure can capture corruption risk in a diverse set of contexts, across markets, countries, and time. Though certainly not an exhaustive list of corruption strategies, it represents a varied collection of simple strategies which are both cheap to use and effective from the perspective of corrupt groups.

The CRI has been shown to be significantly related to both macro and micro measures of corruption (Charron, Dahlström, Fazekas, & Lapuente, 2017). At the EU regional-level, average CRI has a strong negative correlation with the European Quality of Government Index (EQI, $\rho \sim -.54$), and a strong positive correlation with the two subcomponents of the EQI directly measuring corruption risk: corruption perception ($\rho \sim .47$) and reported bribery ($\rho \sim .59$).

At the contract-level, high-CRI contracts have been shown to predict higher prices relative to initial cost estimates across the EU. Moreover, the average CRI of contracts awarded by EU buyers to companies registered in tax havens is higher than those awarded to on-shore companies (Fazekas et al., 2016).

4.2 Measuring contracting network structure: dependent variables

We define three buyer-level outcome measures describing local market structure, *entropy*, *unweighted competitive clustering*, and *weighted competitive clustering*. To measure change over time we define buyer *persistence.*

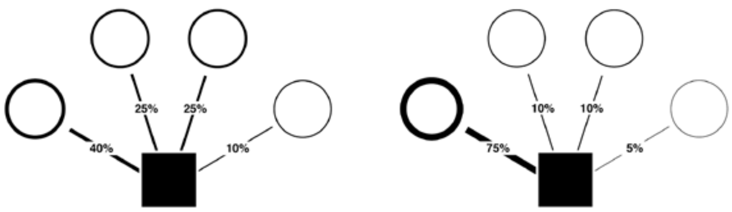
Entropy

For a buyer i, $p_i(j)$ denotes the fraction of i's contract value awarded to supplier j. We calculate the normed entropy of aa buyer's distribution as:

$$H(i) = -\sum_{j \in J} p_i(j) * log(p_i(j)) \,/ log(|J|).$$

The normed entropy of a uniform distribution equals 1. Entropy tends to 0 as the distribution becomes more heterogeneous. In Figure 4, we calculate the entropy of two buyers.

FIGURE 4: TWO HYPOTHETICAL DISTRIBUTIONS OF CONTRACT VALUE



Note: The figure shows two hypothetical distributions of contract value from a buyer (represented by a black square) to four suppliers (represented by circles). The first buyer has normalized entropy 0.32, and the second, reflecting a less equal distribution, has normalized entropy 0.21.

Unweighted competitive clustering

One important local network measure is the clustering coefficient. In most empirical networks, the number of connected triangles is much larger than would be expected than if the nodes were connected at random. In social networks, this phenomenon is often summarized as "a friend of my friend is my friend." For a given node i, its degree k_i, and the count of connections between its neighbors L_i, its clustering coefficient is defined as:

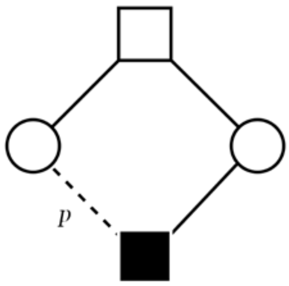
$$C_i = \frac{2L_i}{k_i(k_i - 1)}$$

The clustering coefficient of a node can be interpreted as a probability: given two friends of the node, what is the likelihood that they are friends too? We would like to extend this notion to bipartite networks of buyers and suppliers.

Bipartite networks do not contain triangles. Instead we consider clustering in terms of squares. We interpret the square clustering of a buyer as a probability. Given the focal buyer i, we expect that those suppliers who win from buyers near to i to be much more likely to win from i than suppliers more distant in the network. In a market without favoritism we are more likely to observe a closure phenomenon, as we do in social networks, in which buyers contract with suppliers adjacent to their neighboring institutions much more frequently than at random. All other things being equal, buyers who contract with the same suppliers have some similarity that predicts future contracting behavior.

We visualize this probability as the dotted line edge in Figure 5. In the context of public procurement markets we call this probability *competitive clustering*. Qualitatively, we expect an edge between a buyer (B) and a supplier (S) to be more likely if the supplier S competes with other suppliers (S') which serve the buyer (B), at other buyers (B'). We argue that sharing a supplier implies that the two buyers have some similarity, be it geographical, technical, or political, and that this similarity will manifest more frequently in the sharing of other suppliers.

FIGURE 5: UNWEIGHTED COMPETITIVE CLUSTERING OF THE FOCAL BUYER



Note: Unweighted competitive clustering of the focal buyer, visualized as a black square, is defined as the probability of the dashed edge existing given all other edges in the graph. A second buyer, the white square, and the focal buyer both contract with the supplier on the right. This similarity between the two buyers suggests that if the white buyer also contracts with the buyer on the left, then the focal buyer is much more likely to also contract with that buyer.

Mathematically, we define the competitive clustering of an buyer as the number of four-step paths[2], $C_i(4)$, starting and ending at that buyer, divided by the paths of length three, $P_i(3)$, starting at the buyer:

$$CC_i = \frac{C_i(4)}{P_i(3)}$$

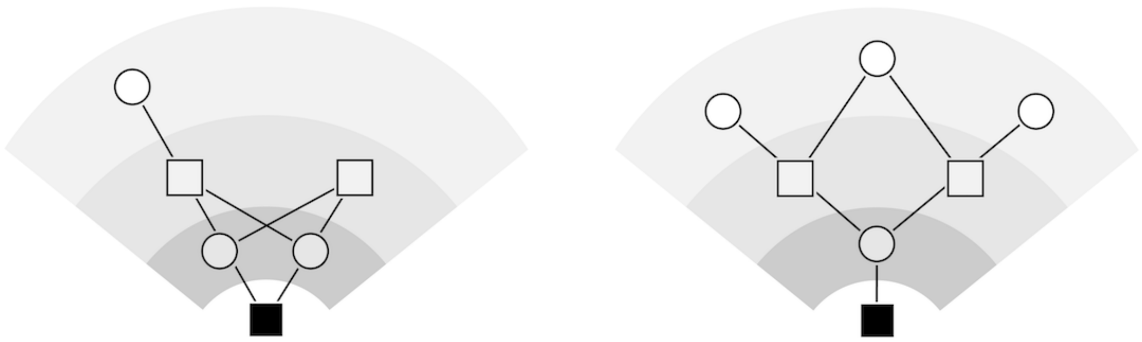
This is a local version of the measure introduced by Robins and Alexander (2004). It is related to the square clustering measure of Lind et al. (2005), which calculates the probability of observing edges between neighbors and second order neighbors of the focal node. It can also be contrasted with

2 In the literature paths starting and ending at the same node are called cycles, hence the notation.

Opsahl's clustering measure (2011), which calculates higher order paths and cycles to create a measure which depends on the connections around triples of nodes from the same bipartite set.

In Figure 6 we calculate two examples of the competitive clustering around a hypothetical buyer, again represented by a black square. Roughly speaking, the more suppliers that are one step away from the focal buyer relative to the number of suppliers that are three steps away, the higher the competitive clustering.

FIGURE 6: THE COMPETITIVE CLUSTERING OF TWO FOCAL BUYERS.



Note: The first buyer has a dense local network - there are many paths of length four starting and ending at the focal buyer. Hence the first buyer has a high competitive clustering of 4/6 = 2/3. The second buyer has a sparse local network and a competitive clustering of 0: no path of length four starting from the black buyer that returns to that buyer.

Weighted competitive clustering

As edge weights, encoding the total contract value and hence the strength of a contracting relationship between a supplier and an buyer, play an important role in our networks we propose a second measures that extends competitive clustering to incorporate edge weights. The measure should equal 1 for a buyer if its competitive clustering is 1 and if the contract values on all edges are homogeneous. Again we count paths of length three from the focal buyer and count how many them return to the buyer to form length four paths. We multiply each path of length four by the geometric mean of its scaled edge weights: this quantity is maximized if the edge weights are identical. As the weights tend to unity, the measure converges to the unweighted competitive clustering measure. Mathematically, count each four-cycle centered at the focal buyer $i$weighted by the geometric mean of the scaled[3] weights in the cycle:

$$CC_i = \frac{C_i(4)}{P_i(3)} * \sum_{j,k,l \in C_i} (w_{ij} w_{jk} w_{kl} w_{il})^{1/4}$$

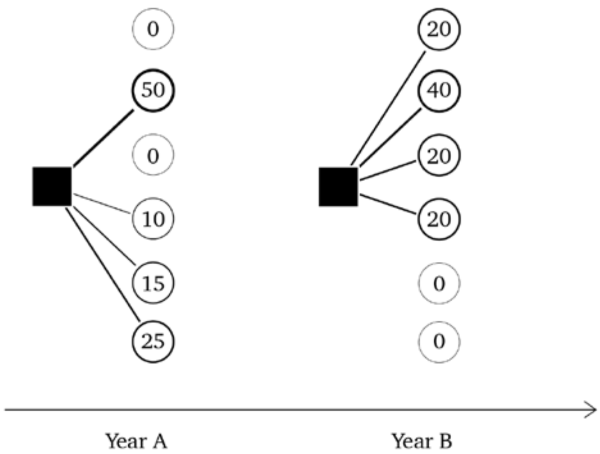
As contract values have great heterogeneity both across the network and locally, we scale the weights dynamically for each buyer weighted competitive clustering calculation by dividing by the maximum edge weight in the 3-node neighbourhood of the buyer.

[3] Within each cycle we scale the weights by dividing each weight by the maximum weight in the cycle.

Persistence

We define buyer network change over time by measuring the correlation of its contract award profile across years. Specifically, we consider all suppliers winning contracts from the buyer in either year A or B or both, and create two vectors: one encoding the distribution of contract value in year A, the other the same for year B. We call the Pearson-correlation[4] of these two vectors the *(A,B)-persistence* (Nicosia et al. 2013) of a buyer. (A,B)-persistence of a buyer is 1 if the buyer's contract awards are distributed according to the same relative contract values to the same suppliers in years A and B. (A,B)-persistence can attain a minimal value of -1 in the case that the issuance of a buyer goes to a completely different set of suppliers in year A compared to year B. We visually demonstrate the concept of persistence in Figure 7.

Figure 7: A buyer's persistence from Year A to Year B



Note: A buyer's persistence from Year A to Year B is measured by the Pearson correlation of its issuances in the two years. The black square again represents the focal buyer at two years. Each circle represents a supplier, and relative positions are fixed across the years. The number represents the percent of the buyer's spending going to that supplier in the specific year. For instance, The first supplier in the list receives 0% of the buyer's contract value in year A, and then 20% in year B. In this case, the buyer's (A,B)-persistence is ρ((0,50,0,10,15,25),(20,40,20,20,0,0)) = 0.38.

5. Methods

5.1 Case selection

We look at public procurement spending in the Czech Republic in 2006-2013 and Hungary in 2009-2014. These two CEE countries provide a good contrast given their very similar levels of development, prevalence of corruption, but contrasting electoral systems and government turnover trajectories. Both countries are successful reformers with GDP per capita converging to the EU average (reaching between 65-75% by the early 2010s). They also score close to the average of the Corruption

[4] Our findings are unchanged if we use Spearman correlation.

Perception Index for CEE EU member states (53.25 in 2013) with scores 48 and 54 respectively on a scale between 0 (corrupt) and 100 (clean) (Transparency International, 2013). Objective corruption proxies in public procurement such as share of single bidder tenders on competitive markets are very similar: 24% and 28% of contracts received a single bid in the Czech Republic and Hungary, respectively in 2009-2014 (Fazekas & Kocsis, 2017). Despite these similarities, recently the countries have seen divergence. Hungary's institutional quality and corruption level has clearly deteriorated since 2010 (Bánkuti, Halmai, & Scheppele, 2012), while the Czech Republic has remained stable, broadly speaking. Public procurement regulatory and administrative systems are very similar in the two countries given the overarching EU framework of the Public Procurement Directives, similarities in national legislation outside of the Directives, and largely identical administrative systems such as electronic public procurement portals[5]. Prior research on corruption and state capture generally grouped the two countries together. To take one such description, both are considered c*ompetitive clientelistic regimes* in which political winners use their office to reward cronies by redistributing public resources including public contracts (Fazekas & Tóth, 2016; Mungiu-Pippidi, 2015).

Crucially for our research design, the Hungarian electoral system allows for and encourages strong majorities, in some cases leading to landslide government turnover. For example, national and local elections are only a few months apart and first-past-the-post electoral rule plays a dominant role (albeit including some elements of proportional representation). These typically lead to one dominant party or coalition taking control at all levels of government. Most recently the right-wing Fidesz party took a 2/3rds majority in parliament and virtually all local government positions in 2010 after eight years in opposition. While in the Czech Republic, there are unaligned elections for the president's office, the two chambers of the national parliament, and both regional and local governments with typically only 1-2 years between them. The Czech Republic has also witnessed an early parliamentary election in 2013 following the collapse of the ruling coalition because of the prime minister's affair with a member of the intelligence services and accusations of bribery. Moreover, the negotiations between parties to form a governing coalition following elections in the Czech Republic take significantly longer than in Hungary, owing in part to proportional representation and the multitude of successful parties. We argue that the differences in electoral systems between the two countries and the corresponding different political incentives they create are exogenous to the corruption risk-contracting network structure relationship we investigate. Hence, cross-country differences in the effect of corruption on network structure can be attributed to differences in electoral competition in the presence of adequate controls.

5.2 Empirical models and identification

To formally test our hypotheses, we employ three scaled dependent variables - described above - at the buyer/year level: i) normalized entropy which is most directly related to H1; ii) logarithm of competitive clustering which is most directly related to H2; and iii) logarithm of weighted competitive clustering which relates to both H1 and H2. H3 and H4 are tested in regression models using all three dependent variables. Additionally, for H3, we also conduct statistical tests for the equality of group means using Monte Carlo random permutation simulations in which supplier persistence is our main dependent variable.

[5] For a structured comparison of all EU countries' legislation and institutions see: http://europam.eu/ and for a review of data and IT systems see Cingolani et al, 2015.

For each country and each dependent variable we run two regression models: a pooled OLS model and a buyer fixed effects panel data model (random effects specification was rejected in all cases by Hausman test). We consider only those buyers with at least five contracts in our data set to exclude the smaller organisations whose behaviour is noisier. We find similar results, documented in Appendix A, when we restrict to buyers with at least 10 contracts. In both cases, the dependent variables are calculated on the full networks.

The panel data equation we estimated is

$$y_{i,t} = \beta_1 * CRI_{i,t} + \beta_2 X_{i,t} + \alpha_i + e_{i,t}$$

Where $y_{i,t}$ is the dependent variable observed for buyer i at time t, CRIi,t is our main independent variable, the measure of corruption risks, $X_{i,t}$ is the matrix of control variables, $\alpha_i$is the time-invariant individual buyer effect, and $e_{i,t}$is the error term. The matrix of control variables contained the following indicators:

- The log of number of contracts awarded by the buyer in that year.
- The log of the total value of contracts awarded by the buyer in that year.
- An election year dummy: 1 if the year in question had a parliamentary election in that country results in a change in government.
- The interaction of CRI and the election year dummy.
- Year dummies.
- Buyer type, distinguishing between local and central government institutions, provided by the public procurement registry (only in pooled OLS).
- Buyer location, based on the NUTS-II classification (only in pooled OLS).
- Buyer sector (*Hungary-only*), describing the primary sector of the buyer, provided by the public procurement registry (only in pooled OLS).

In the absence of an experimental setting, the buyer-level fixed effects panel data models provide a reliable and valid estimate of the hypothesized causal effects for several reasons. First, they control for unobserved organizational characteristics such as spending preferences influencing supplier composition (e.g. taste for high quality goods). Second, year dummies control for common shocks occurring over time separately in each of the countries. Third, indicators of time varying organizational characteristics such as total value and number of contracts awarded and sectoral composition of spending control of obvious confounding factors simultaneously determining market structure as well as corruption risks. Fourth, our analysis is based on the full sample of government contracting activities barring few highly specific spending lines such as defense contracts with national security implications. This means that sampling bias poses little threat to identification, a challenge which often limits the generalizability of experimental and quasi-experimental designs. Fifth, the corruption and network measures are constructed from different micro variables on different measurement levels minimizing the risk of double-counting the same phenomena on both sides of the equation. Crucially, we only consider contracts awarded on competitive markets, defined as having at least 3 active suppliers, which implies that the supplier pool would allow open and fair competition to take place (e.g. monopolistic markets determined by technology do not bias results).

Our regressions are run using the plm package of the R programming language (Croissant and Millo, 2008). To account for possible cross-sectional correlation in the error structure, we report panel-corrected standard errors, calculated using the method of Beck and Katz (1995). As a check against the potential non-independence of observations in the contracting network, we simulate p-values using Monte Carlo random permutations, see Appendix B (Good, 2006). Finally, in Appendix C we show the results of the competitive clustering models with year fixed-effects included to control for common temporal shocks, while excluding the election year – corruption interaction which cannot be entered simultaneously.

6. Results

6.1 Uneven spending distribution: Entropy

With regards to H1, we find limited evidence that CRI impacts buyer entropy in either country, shown in Table 4. Though both pooled OLS models show a statistically significant negative effect of CRI on entropy as expected; the more reliable fixed-effects panel data models do not support this conclusion as effects are insignificant and very small.

TABLE 4. POOLED OLS AND BUYER FIXED-EFFECTS REGRESSION MODELS PREDICTING BUYER ENTROPY. WE REPORT PANEL-CORRECTED STANDARD ERRORS.

	Dependent Variable: Buyer Entropy, >=5 Contracts			
	Hungary		Czech Republic	
	(1)	(2)	(3)	(4)
CRI	-.009°	.002	-.014*	-.004
	(.005)	(.005)	(.006)	(.006)
Election Year Dummy	-.038***	-.016	-.012	-.005
	(.011)	(.010)	(.011)	(.010)
Buyer Number of Contracts (log)	.044***	.077***	.044***	.057***
	(.006)	(.007)	(.005)	(.006)
Buyer Contract Value (log)	-.053***	-.103***	-.045***	-.096***
	(.003)	(.004)	(.003)	(.004)
CRI, Election Year Interaction	-.029**	-.018°	-.016	-.022
	(.010)	(.011)	(.016)	(.015)
Constant	1.285***		1.222***	
	(.045)		(.043)	
Model	Pooled OLS	Buyer FE	Pooled OLS	Buyer FE
Type, Location, Sector+ Dummies	Yes	-	Yes	-
Observations	3,657	3,657	2,704	2,704
R^2	.145	.248	.115	.209
F Statistic	20.448*** (df = 30; 3626)	121.052*** (df = 5; 1838)	18.312*** (df = 19; 2684)	95.737*** (df = 5; 1813)

Note: +Sector only available for Hungary
°p<.1; *p<.05; **p<.01;***p<.001

The lack of clear support for H1 is perhaps not surprising, given for example the recent research on political-economic networks in Hungary suggesting that missing business connections are driving market outcomes (Stark & Vedres, 2012). Our dependent variable in these models is entropy amongst the winners of the buyer's awarded contracts which is a biased measure of corruption in as much as it neglects those suppliers which have been totally excluded from the market. This bias increases as total exclusion becomes the dominant effect of corruption potentially leading to weak and insignificant regression results. Hence, we now turn to models which take an outcome variable explicitly incorporating full exclusion too.

6.2 Excluding non-favoured suppliers: Competitive clustering

This analysis, summarized in Table 5, leads to three notable insights (findings are also confirmed by Monte Carlo random permutation simulations in Appendix B and the inclusion of year dummies in Appendix C). First, with regards to H2, our regression models provide clear support for our hypothesized empirical relationship. In both countries, every model specification shows a significant negative relationship between CRI and competitive clustering. This means that corruption in both countries appear to lead to outright exclusion in buyers' local markets. Combined with the above finding that CRI doesn't predict entropy, the significant impact of CRI on competitive clustering underlines that observed reconfigurations of market relationships are much less characteristics of these corrupt environments; rather corruption in these countries is very much about missing local connections in contracting networks. Such interpretation bodes well with macro-institutional accounts of competitive clientelistic regimes where the rule of the game is whoever gains control of government uses it to divide the spoils within its own camp and leaving close to nothing to the losers of the political competition (Mungiu-Pippidi, 2015). That is corruption functions as a mechanism for total exclusion.

Second, we also find that in all models, effect sizes are larger in Hungary than in the Czech Republic: roughly 1.5-2 times larger impact of corruption on market structure. Note that all variables are standardized so cross-country differences are not down to variable scaling differences. While H4 is the hypothesis which we can test in a least tight-knit fashion, these cross-country differences lend some support to our theory.

Third, the interaction term between CRI and the election year dummy is not significant in either model, indicating that the there is no difference in the relationship between corruption risk and competitive clustering during years that see a change in government compared to those without. This indicates that, if changes in government result in a significant change in buyer behavior, it is not observable within the same year of the change in government. Hence, the simplest test does not lend support to hypothesis H3.

TABLE 5. POOLED OLS AND BUYER FIXED-EFFECTS REGRESSION MODELS PREDICTING BUYER COMPETITIVE CLUSTERING. WE REPORT PANEL-CORRECTED STANDARD ERRORS.

	Dependent Variable: Buyer Competitive Clustering, >=5 Contracts			
	Hungary		Czech Republic	
	(1)	(2)	(3)	(4)
CRI	-.072***	-.046***	-.024***	-.029***
	(.005)	(.005)	(.006)	(.006)
Election Year Dummy	.023*	.031**	-.013	-.028**
	(.011)	(.010)	(.010)	(.009)
Buyer Number of Contracts (log)	.137***	.102***	.158***	.148***
	(.006)	(.007)	(.006)	(.006)
Buyer Contract Value (log)	-.015***	.002	.003	.004
	(.003)	(.004)	(.003)	(.004)
CRI, Election Year Interaction	-.021*	-.002	.007	.005
	(.010)	(.010)	(.014)	(.014)
Constant	.029		-.137**	
	(.050)		(.047)	
Model	Pooled OLS	Buyer FE	Pooled OLS	Buyer FE
Type, Location, Sector+ Dummies	Yes	-	Yes	-
Observations	3,657	3,657	2,704	2,704
R^2	.424	.192	.463	.306
F Statistic	88.934*** (df = 30; 3626)	87.276*** (df = 5; 1838)	121.604*** (df = 19; 2684)	159.898*** (df = 5; 1813)

Note: +Sector only available for Hungary
°p<.1; *p<.05; **p<.01;***p<.001

To further bridge the different degrees of market structure reconfiguration resulting from corruption, that is explore the overlaps between H1 and H2, we also consider weighted competitive clustering as an outcome variable. Weighted competitive clustering measures both the exclusion and heterogeneity in the observed contract value distributions, hence aims to reflect both H1 and H2. We find results similar to the unweighted competitive clustering case across all four models (Table 6), suggesting that the unweighted competitive clustering results are robust to noise and edge weight heterogeneity and also that H1 has some empirical support. To reiterate, CRI has a significant negative coefficient predicting weighted competitive clustering, effect sizes are consistently larger in Hungary than in the Czech Republic, and years with government change do not substantially change the relationship between CRI and clustering.

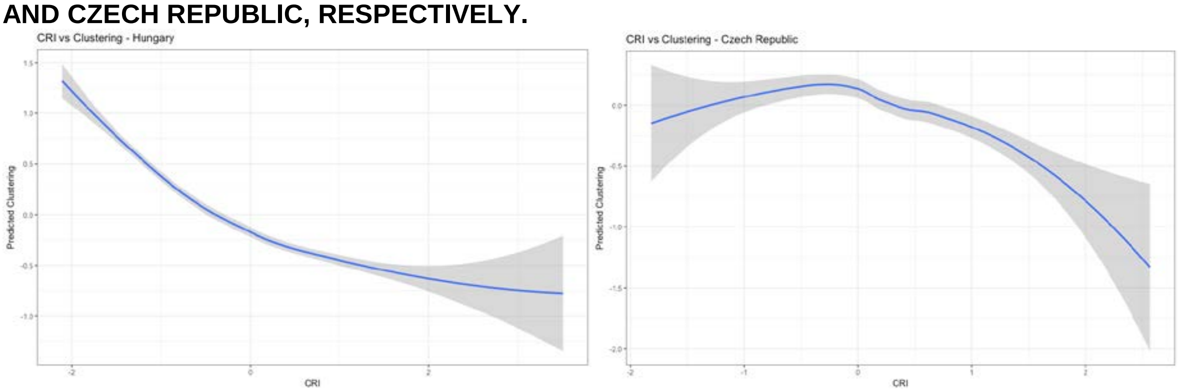
TABLE 6. POOLED OLS AND BUYER FIXED-EFFECTS REGRESSION MODELS PREDICTING BUYER COMPETITIVE CLUSTERING. WE REPORT PANEL-CORRECTED STANDARD ERRORS.

	Dependent Variable: Buyer Weighted Competitive Clustering, >=5 Contracts			
	Hungary		Czech Republic	
	(1)	(2)	(3)	(4)
CRI	-.064***	-.047***	-.012*	-.014*
	(.005)	(.005)	(.006)	(.006)
Election Year Dummy	.016	.020°	.020°	.005
	(.010)	(.010)	(.010)	(.010)
Buyer Number of Contracts (log)	.094***	.070***	.090***	.080***
	(.006)	(.007)	(.005)	(.006)
Buyer Contract Value (log)	-.003	.010*	.017***	.021***
	(.003)	(.004)	(.003)	(.004)
CRI, Election Year Interaction	.001	.015	-.005	-.015
	(.010)	(.011)	(.015)	(.014)
Constant	-.035		-.207***	
	(.046)		(.044)	
Model	Pooled OLS	Buyer FE	Pooled OLS	Buyer FE
Type, Location, Sector+ Dummies	Yes	-	Yes	-
Observations	3,657	3,657	2,704	2,704
R^2	.315	.114	.300	.142
F Statistic	55.585*** (df = 30; 3626)	47.269*** (df = 5; 1838)	60.461*** (df = 19; 2684)	59.970*** (df = 5; 1813)
Note:				+Sector only available for Hungary °p<.1; *p<.05; **p<.01;***p<.001

Despite the insignificant relationship between CRI and entropy, the significant relationship between CRI and weighted competitive clustering lends some support to hypothesis H1. The evidence so far jointly suggests that full exclusion is the rule of the game with some degree of partial exclusion also present. While we cannot explore the exact reasons for the presence of both mechanisms, we posit that in markets where non-favoured suppliers command unique skills and capacities, their total exclusion would be counterproductive even if total exclusion is typically the norm. In a practical sense, even a tender tailored to a specific supplier may be won by an outsider. The red flags of the CRI are merely strategies of corrupt contract allocation; they do not fully secure the tender for any favoured supplier.

To better demonstrate the importance of these findings, we plot the model predictions for competitive clustering as a function of CRI for each country using the fixed-effects model (models (2) and (4) in Table 5) and a LOESS smoother in Figure 8. We standardized both competitive clustering and CRI. In Hungary increasing CRI from one standard deviation below the mean to one standard deviation above it decreases competitive clustering by approximately one standard deviation, in other words one standard deviation of CRI decreases competitive clustering by half a standard deviation. In the Czech Republic, a one standard deviation increase in CRI results in about a third of a standard deviation decrease in competitive clustering.

FIGURE 8: PLOTTING THE LOESS-SMOOTHED PREDICTED EFFECTS OF CRI ON COMPETITIVE CLUSTERING FROM THE FIXED-EFFECTS MODELS (MODELS (2) AND (4)) IN TABLE 5 FOR HUNGARY AND CZECH REPUBLIC, RESPECTIVELY.



How can we relate this to a concrete market outcome? A one standard deviation increase in CRI is approximately the same as having one more red flag, on average. In the Hungarian case, this means that if a buyer has one more red flag on average, its competitive clustering will be half a standard deviation lower. Ceteris paribus, a one standard deviation decrease in competitive clustering means having three fewer suppliers. In Hungary, an additional red flag on average means that a buyer contracts with 1.5 fewer suppliers in a given year. The same analysis in the Czech Republic indicates that an additional red flag on average means around 1 fewer supplier per year. The average buyer in each country has around 10 suppliers per year. In other words, an additional red flag per year means roughly a 10-15% decrease in the number of suppliers a buyer contracts with.

6.3 Government change: Captured buyers and persistence

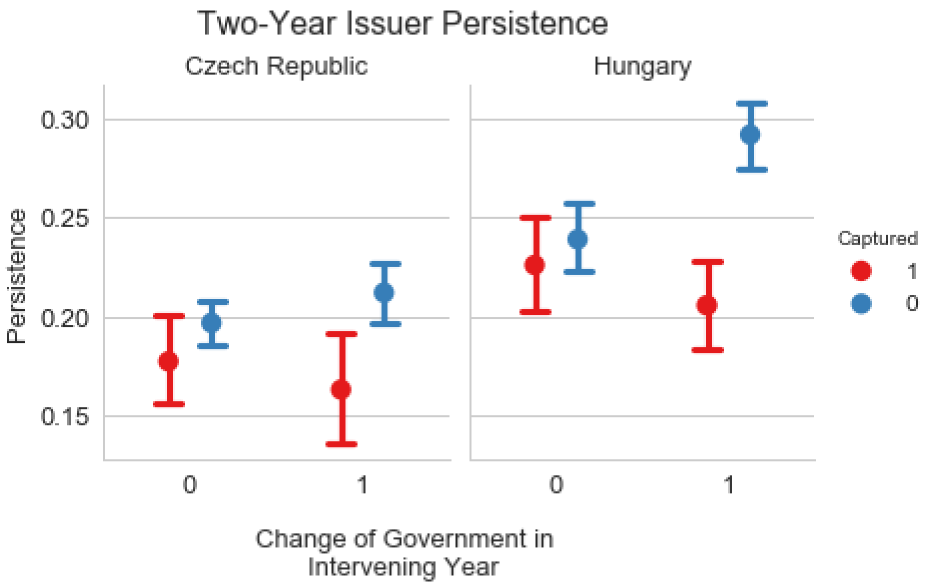
Having established the link between CRI and the topology of a buyer's network neighborhood via competitive clustering, we now return to H3 by probing the impact of government change in greater detail. A crucial aspect of corrupting contracting market structure is that it not only influences the overall market configuration, but also which companies stay and go in those markets, that is corruption is personal as opposed to impersonal market forces. To this end we use the above defined persistence indicator as dependent variable.

To contrast very different corruption realities within countries, we define buyers as *captured* if they have above average CRI and below average competitive clustering in a year and non-captured otherwise. Then contrasting captured and non-captured buyers' persistence throughout periods of government change directly tests H3. When governments change, we expect captured, that is highly corrupt organisations which tend to exclude, to experience a drop in contracting persistence due to the shock to their personal, corrupt network's access to power. The opposite is true of buyers with more impersonal, open contracting relationships.

We continue to use an annual time frame, and consider changes in buyer behavior across years. We analyze pairs that are two years apart to capture the effect of an intervening government change. For example, we are interested in the (2009,2011)-persistence of Hungarian buyers, as 2010 saw a change in government. Hence, we will refer to two-year difference persistence simply as persistence for the rest of the paper.

To test H3, we investigate buyer persistence for each country in greater detail. We group captured and non-captured buyers and plot the distributions of persistences across regular years and change of government years[6] in Figure 9. Comparing the persistences of captured vs non-captured buyers across normal and politically volatile years reveals a clear picture in line with H3. We see that in both countries, the persistence of captured buyers is generally lower than that of non-captured buyers in periods with government change while differences in persistence are statistically indistinguishable in periods without government change. In Hungary, the persistence of captured buyers across government change periods is drastically lower than that of non-captured buyers, suggesting that politics has an outsized influence on these buyers. In the Czech Republic, the impact of capture is much smaller again lending some support to our hypothesis on cross-country differences (H4).

FIGURE 9. COMPARISON OF PERSISTENCE OF CAPTURED AND NON-CAPTURED BUYERS ACROSS YEARS WITH AND WITHOUT GOVERNMENT CHANGE



Note: Captured buyers are defined as those with high CRI and low competitive clustering. Persistence is defined as the correlation of the buyer's issuance of contract value to suppliers over two years (e.g. 2009 to 2011).

We verify the significance of the observed differences using a permutation test (Good, 2006). We randomly shuffle the capture category labels 1000 times and recalculate the difference in persistence between captured and non-captured buyers. We calculate a p-value by counting the number of times the randomized captured vs non-captured persistence difference is less than the real difference, that is we compare the observed empirical relationship to a truly random distribution of the capture label to establish the likelihood of it arising from a genuinely random as opposed to causal process.

In Table 7 we see that captured buyers are significantly less persistent across the 2010 Hungarian change in government. Although, quite interestingly, they are also significantly less persistent from 2012 to 2014. The effect size of buyer capture is by far the largest in the 2009-2011 period with government change in the middle while it is also significant and sizeable across the 2010-2012 period suggesting an extended impact of government change on rewiring particularistic network relationships. This most likely reflects the length of time needed for corrupt elites to take full control of public

[6] We plot the year-by-year persistences of captured and non-captured buyers in Appendix D

procurement markets by rewiring contracting networks fully in line with their particularistic company connections. Captured Hungarian buyers have 38% weaker correlation in their issuance profiles across the change in government than their non-captured peers.

TABLE 7: HUNGARIAN BUYER TWO-YEAR PERSISTENCE PERMUTATION TEST

Years	Observed Difference	% Difference	p-value
2009,2011	-0.151	-38%	<.001***
2010,2012	-0.051	-14%	.0013***
2011,2013	0.014	+4%	.7559
2012,2014	-0.044	-12%	.0198**

P-values: *** <.01, **<.05 , *<.10
Note: observed difference between captured and non-captured buyers and significance of the difference according to a label-permuted nonparametric test of differences.

In the Czech Republic, shown in Table 8, we also see the strongest negative effect of capture on persistence in the years across the change in government in 2010: 2008-2010, 2009-2011, and 2010-2012. Like for Hungary, the effect is significant for an extended period, again reflecting the length of time needed for full corrupt control. We also show histograms of the randomized persistences and the actual persistence for each year in Appendix E.

TABLE 8: CZECH BUYER TWO-YEAR PERSISTENCE PERMUTATION TEST

Years	Difference	% Difference	p-value
2006,2008	0.004	+2%	0.57
2007,2009	-0.030	-11%	0.112
2008,2010	-0.045	-17%	0.029**
2009,2011	-0.052	-21%	0.007***
2010,2012	-0.047	-16%	0.020**
2011,2013	0.007	+2%	0.639

P-values: ***<.01,**<.05, *<.10
Note: observed difference between captured and non-captured buyers and significance of the difference according to a label-permuted nonparametric test of differences.

We suggest that these findings represent strong evidence for H3 on the effect of government change on temporally dismantling corrupt contacting networks. In addition, they also reveal the existence of politically-driven state capture among public buyers in both countries, and that CRI together with network topology are a useful identifier of this complex phenomenon.

Like in regression models, the effects are much stronger in Hungary than in the Czech Republic lending indicative support for H4. Captured Hungarian buyers change about one and a half times as much across elections relative to a randomized benchmark as captured Czech buyers. Given that Hungary and the Czech Republic are about equally corrupt, we could find evidence for electoral contestation limiting the cost of corruption even if it fails to shift corruption norms, something the literature has focused on.

7. Conclusions

This paper analyses the connection between corruption and market structure in public procurement markets. We use a network science framework to test qualitative hypotheses from the literature on corruption in a quantitative setting. Specifically, we find strong evidence at the micro-level that corruption in public procurement is predominantly about the exclusion of suppliers. This is in line with theories of corruption as particularism, or the preferential treatment of certain groups by the state. Back-of-the-envelope calculations suggest that at the margin, if a buyer awards contracts with an additional red flag on average, it will contract with 10-15% fewer unique suppliers. Relating back to our theory, these missing connections are the manifestation of corrupt behaviour distorting market structure.

We validate the political nature of the inverse relationship between corruption and competitive clustering by observing that buyers with high CRI and low competitive clustering, which we refer to as captured, see significantly larger changes in their contracting relationships across government changes than other buyers. In Hungary, the correlation of contract awards of a captured buyer across an election year is 38% weaker than a non-captured buyer (that is fewer overlaps in the companies contracted in one year to another). In the Czech Republic this effect is 21%, or about half of the effect as in Hungary.

We suggest that our work has wider implications. For the literature on corruption and state capture, our findings provide empirical evidence about the mechanisms of corrupt allocation of government resources. For policymakers, our approach suggests that networks can visualize clusters of corruption risk. Simply looking at networks can reveal the structure of buyer-supplier relationships in a way that traditional statistical analysis cannot. The network framework also suggests a novel approach to corruption detection: looking for missing edges. Finally, our paper makes the broader point that electoral contestation and power sharing carry the potential to mitigate corrupt market distortions even in systematically corrupt places. That is, even if corruption is widespread, its power to reconfigure market relationships hence to impose economic costs on markets varies according to political constraints.

We also identified several drawbacks to our approach, some of which provide suggestions for future work. First, we consider only two countries - clearly our work can be extended to many more countries. Second, our network measure of competitive clustering is a simple measure and we posit a simple relationship between local network density and corruption. In general corrupt groups of buyers and suppliers may form larger highly dense cliques (Fazekas & Tóth, 2016). This problem is compounded by the fact that our data does not contain information on the individuals in charge of or benefiting from the buyers and suppliers. Hungarian and Czech media are full of examples of suspected corrupt oligarchs with many companies and affiliations.

Third, we could not offer a direct measure of social costs of corruption arising due to market distortions. Further work could build on our findings and explicitly model market prices and social costs associated with corruption market distortions.

References

Aidt, T. (2016). Rent seeking and the economics of corruption. *Constitutional Political Economy*, *27*(2), 142–157.

Albert, R., & Barabási, A. L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics*, *74*(1), 47.

Baldi, S., Bottasso, A., Conti, M., & Piccardo, C. (2016). To bid or not to bid: That is the question: Public procurement, project complexity and corruption. *European Journal of Political Economy*, *43*, 89–106. http://doi.org/10.1016/j.ejpoleco.2016.04.002

Bánkuti, M., Halmai, G., & Scheppele, K. L. (2012). Disabling the Constitution. *Journal of Democracy*, *23*(3), 138–146. http://doi.org/10.1353/jod.2012.0054

Beck, N., & Katz, J. N. (1995). What to do (and not to do) with time-series cross-section data. *American political science review*, *89*(3), 634-647.

Beekman, G., Bulte, E. H., & Nillesen, E. E. M. (2013). Corruption and economic activity: Micro level evidence from rural Liberia. *European Journal of Political Economy*, *30*, 70–79. http://doi.org/10.1016/j.ejpoleco.2013.01.005

Blackburn, K., & Forgues-Puccio, G. F. (2009). Why is corruption less harmful in some countries than in others? *Journal of Economic Behavior & Organization*, *72*(3), 797–810. http://doi.org/10.1016/j.jebo.2009.08.009

Borgatti, S. P., Mehra, A., Brass, D. J., & Labianca, G. (2009). Network analysis in the social sciences. *science*, *323*(5916), 892-895.

Broms, R., Dahlström, C., & Fazekas, M. (2017). *Political competition and public procurement quality* (QoG Working Paper Series No. 2017:). Gothenburg.

Charron, N., Dahlström, C., Fazekas, M., & Lapuente, V. (2017). Careers, Connections, and Corruption Risks: Investigating the impact of bureaucratic meritocracy on public procurement processes. *Journal of Politics*, *79*(1), 89–103.

Charron, N., Dijkstra, L., & Lapuente, V. (2015). Mapping the Regional Divide in Europe: A Measure for Assessing Quality of Government in 206 European Regions. *Social Indicators Research*, *122*(2), 315–346.

Coviello, D., & Gagliarducci, S. (2017). Tenure in Office and Public Procurement. *American Economic Journal: Economic Policy*, *forthcomin*.

Coviello, D., & Mariniello, M. (2014). Publicity requirements in public procurement: Evidence from a regression discontinuity design. *Journal of Public Economics*, *109*, 76–100.

Croissant, Y., & Millo, G. (2008). Panel data econometrics in R: The plm package. Journal of Statistical Software, 27(2), 1-43.

Czibik, Á., Tóth, B., & Fazekas, M. (2015). *How to Construct a Public Procurement Database from Administrative Records?* (GTI-R/2015:02).

Dávid-Barrett, E., & Fazekas, M. (2016). *Corrupt contracting: Controlling Partisan Favouritism in Public Procurement* (ERCAS Working Paper No. 49). Berlin.

Diwan, I., Keefer, P., & Schiffbauer, M. (2016). *Pyramid Capitalism. Cronyism, Regulation, and Firm Productivity in Egypt* (IDB Working Paper Series No. 739). Washington, DC.

Eggers, A. C. (2014). Partisanship and Electoral Accountability: Evidence from the UK Expenses Scandal. *Quarterly Journal of Political Science*, *9*(4), 441–472. http://doi.org/10.1561/100.00013140

Fazekas, M., Chvalkovská, J., Skuhrovec, J., Tóth, I. J., & King, L. P. (2014). Are EU funds a corruption risk? The impact of EU funds on grand corruption in Central and Eastern Europe. In A. Mungiu-

Pippidi (Ed.), *The Anticorruption Frontline. The ANTICORRP Project, vol. 2.* (pp. 68–89). Berlin: Barbara Budrich Publishers.

Fazekas, M., & Kocsis, G. (2017). Uncovering High-Level Corruption: Cross-National Corruption Proxies Using Government Contracting Data. *British Journal of Political Science*, available online: https://www.cambridge.org/core/journals/british-journal-of-political-science/article/uncovering-highlevel-corruption-crossnational-objective-corruption-risk-indicators-using-public-procurement-data/8A1742693965AA92BE4D2BA53EADFDF0 .

Fazekas, M., & Tóth, I. J. (2016). From corruption to state capture: A new analytical framework with empirical applications from Hungary. *Political Research Quarterly*, *49*(2), 320–334.

Fazekas, M., Tóth, I. J., & King, L. P. (2016). An Objective Corruption Risk Index Using Public Procurement Data. *European Journal of Criminal Policy and Research*, *22*(3), 369–397.

Freund, C., Nucifora, A., & Rijkers, B. (2014). *All in the family : state capture in Tunisia* (Policy Research working paper No. WPS 6810). Washington, DC.

Goldman, E., Rocholl, J., & So, J. (2013). Politically Connected Boards of Directors and The Allocation of Procurement Contracts. *Review of Finance*, *17*(5), 1617–1648. http://doi.org/10.1093/rof/rfs039

Good, P. I. (2006). *Resampling Methods A Practical Guide to Data Analysis* (3rd editio). Berlin: Birkhauser.

Goyal, S. (2012). *Connections: An Introduction to the Economics of Networks*. Princeton, NJ: Princeton University Press.

Hessami, Z. (2014). Political corruption, public procurement, and budget composition: Theory and evidence from OECD countries. *European Journal of Political Economy*, *34*, 372–389. http://doi.org/10.1016/j.ejpoleco.2014.02.005

Hudon, P.-A., & Garzón, C. (2016). Corruption in public procurement: entrepreneurial coalition building. *Crime, Law and Social Change*, *66*(3), 291–311. http://doi.org/10.1007/s10611-016-9628-4

Jackson, M. O. (2010). *Social and Economic Networks*. Princeton, NJ: Princeton University Press.

Jackson, M. O., Rogers, B. W., & Zenou, Y. (2017). The Economic Consequences of Social-Network Structure. *Journal of Economic Literature*, *55*(1), 49-95.

Knack, S., Biletska, N., & Kacker, K. (2017). *Deterring Kickbacks and Encouraging Entry in Public Procurement Markets. Evidence from Firm Surveys in 88 Developing Countries* (Policy Research Working Paper No. 8078). Washington, DC.

Kirman, A. (2010). *Complex economics: individual and collective rationality*. Routledge.

Larcinese, V., & Sircar, I. (2017). Crime and punishment the British way: Accountability channels following the MPs' expenses scandal. *European Journal of Political Economy*, *47*, 75–99.

Lewis-Faupel, S., Neggers, Y., Olken, B. A., & Pande, R. (2016). Can Electronic Procurement Improve Infrastructure Provision? Evidence from Public Works in India and Indonesia. *American Economic Journal: Economic Policy*, *8*(3), 258–283.

Lind, P. G., Gonzalez, M. C., & Herrmann, H. J. (2005). Cycles and clustering in bipartite networks. *Physical review E*, *72*(5), 056127.

Mauro, P. (1998). Corruption and the composition of government expenditure. *Journal of Public Economics*, *69*, 263–279.

Mungiu-Pippidi, A. (2015). *The Quest for Good Governance. How Societies Develop Control of Corruption*. Cambridge, UK: Cambridge University Press.

Neto, F. B., Gerring, J., Hicken, A., Knutsen, C. H., Bernhard, M., Skaaning, S.-E., … Lindberg, S. (2015). *Party Strength and Economic Growth* (V-Dem Working Papers No. 2015:10). Gothenburg.

Nicosia, V., Tang, J., Mascolo, C., Musolesi, M., Russo, G., & Latora, V. (2013). Graph metrics for temporal networks. In *Temporal networks* (pp. 15-40). Springer Berlin Heidelberg.

North, D. C., Wallis, J. J., & Weingast, B. R. (2009). *Violence and Social Orders. A Conceptual Framework for Interpreting Recorded Human History*. Cambridge, UK: Cambridge University Press.

OECD. (2007). *Integrity in Public Procurement. Good Practice from A to Z*. Paris: OECD.

OECD. (2015). *Government at a glance. 2015*. Paris: OECD.

Olken, B. A. (2007). Monitoring Corruption: Evidence from a Field Experiment in Indonesia. *Journal of Political Economy*, *115*(2), 200–249.

Opsahl, T. (2013). Triadic closure in two-mode networks: Redefining the global and local clustering coefficients. *Social Networks*, *35*(2), 159-167.

Pricewaterhouse Coopers. (2013). *Identifying and reducing corruption in public procurement in the EU*. Brussels: PricewaterhouseCoopers and Ecorys.

Rauch, J. E., & Casella, A. (Eds.). (2001). *Networks and markets*. Russell Sage Foundation.

Rose-Ackerman, S. (2015). Are Corrupt Elites Neccessary for Corrupt Countries? In C. Dahlström & L. Wangnerud (Eds.), *Elites, Institutions and the quality of government* (pp. 33–48). New York: Palgrave Macmillan.

Rothstein, B., & Teorell, J. (2008). What Is Quality of Government? A Theory of Impartial Government Institutions. *Governance*, *21*(2), 165–190.

Schweitzer, F., Fagiolo, G., Sornette, D., Vega-Redondo, F., Vespignani, A., & White, D. R. (2009). Economic networks: The new challenges. *science*, *325*(5939), 422-425.

Shleifer, A., & Vishny, R. W. (1993). Corruption. *The Quarterly Journal of Economics*, *108*(3), 599–617.

Stark, D., & Vedres, B. (2012). Political Holes in the Economy: The Business Network of Partisan Firms in Hungary. *American Sociological Review*, *77*(5), 700–722.

Transparency International. (2013). *Global Corruption Barometer 2013*. Berlin: Transparency International.

World Bank. (2009). *Fraud and Corruption. Awareness Handbook*. Washington DC: World Bank.

Wright, J. (2008). To Invest or Insure? How Authoritarian Time Horizons Impact Foreign Aid Effectiveness. *Comparative Political Studies*, *41*(7), 971–1000. http://doi.org/10.1177/0010414007308538

Appendices

Appendix A - Robustness checks with higher contracting threshold.

TABLE A1: POOLED OLS AND BUYER FIXED-EFFECTS MODELS FOR ENTROPY OF BUYERS ISSUING AT LEAST 10 CONTRACTS.

	Dependent Variable: Buyer Entropy, >=10 Contracts			
	Hungary		Czech Republic	
	(1)	(2)	(3)	(4)
CRI	-.003	.004	-.006	.007
	(.006)	(.007)	(.008)	(.008)
Election Year Dummy	-.015	.018	$-.030^{*}$	-.005
	(.013)	(.012)	(.013)	(.012)
Buyer Number of Contracts (log)	$.065^{***}$	$.082^{***}$	$.040^{***}$	$.049^{***}$
	(.007)	(.009)	(.007)	(.008)
Buyer Contract Value (log)	$-.074^{***}$	$-.122^{***}$	$-.046^{***}$	$-.107^{***}$
	(.004)	(.005)	(.004)	(.005)
CRI, Election Year Interaction	.003	.012	-.003	$-.031^{\circ}$
	(.013)	(.013)	(.018)	(.017)
Constant	1.551^{***}		1.237^{***}	
	(.055)		(.051)	
Model	Pooled OLS	Buyer, Year FE	Pooled OLS	Buyer, Year FE
Type, Location, Sector+ Dummies	Yes	-	Yes	-
Observations	1,806	1,806	1,491	1,491
R^2	.280	.362	.163	.286
F Statistic	23.035^{***} (df = 30; 1775)	107.624^{***} (df = 5; 948)	15.876^{***} (df = 18; 1472)	82.333^{***} (df = 5; 1030)

Note: +Sector only available for Hungary

$^{\circ}p<.1$; $^{*}p<.05$; $^{**}p<.01$, $^{***}p<.001$

TABLE A2: POOLED OLS AND BUYER FIXED-EFFECTS MODELS FOR COMPETITIVE CLUSTERING OF BUYERS ISSUING AT LEAST 10 CONTRACTS.

	Dependent Variable: Buyer Competitive Clustering, >=10 Contracts			
	Hungary		Czech Republic	
	(1)	(2)	(3)	(4)
CRI	-.069***	-.039***	-.023**	-.026***
	(.007)	(.007)	(.009)	(.008)
Election Year Dummy	.014	.039**	-.041**	-.052***
	(.016)	(.014)	(.013)	(.011)
Buyer Number of Contracts (log)	.131***	.110***	.145***	.132***
	(.009)	(.009)	(.009)	(.007)
Buyer Contract Value (log)	.002	-.002	.003	.004
	(.005)	(.005)	(.005)	(.005)
CRI, Election Year Interaction	-.018	.002	.027	.027°
	(.016)	(.015)	(.019)	(.016)
Constant	-.147*		-.110	
	(.075)		(.068)	
Model	Pooled OLS	Buyer FE	Pooled OLS	Buyer FE
Type, Location, Sector+ Dummies	Yes	-	Yes	-
Observations	1,806	1,806	1,491	1,491
R^2	.407	.180	.427	.289
F Statistic	40.660*** (df = 30; 1775)	41.569*** (df = 5; 948)	60.951*** (df = 18; 1472)	83.902*** (df = 5; 1030)

Note: +Sector only available for Hungary

°p<.1; *p<.05; **p<.01;***p<.001

Government Transparency Institute

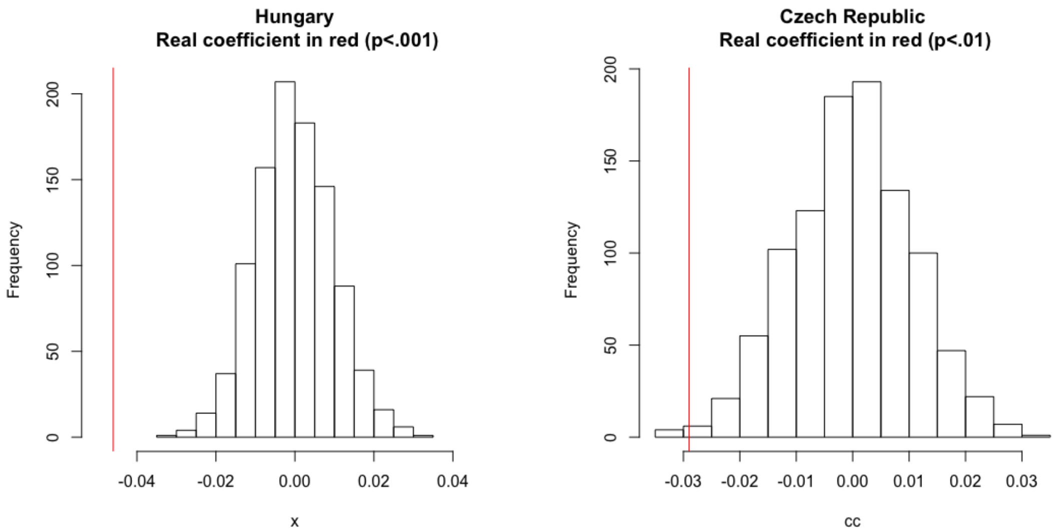
TABLE A3: POOLED OLS AND BUYER FIXED-EFFECTS MODELS FOR WEIGHTED COMPETITIVE CLUSTERING OF BUYERS ISSUING AT LEAST 10 CONTRACTS.

	Dependent Variable: Buyer Weighted Competitive Clustering, >=10 Contracts			
	Hungary		Czech Republic	
	(1)	(2)	(3)	(4)
CRI	$-.057^{***}$	$-.034^{***}$	-.007	-.003
	(.006)	(.007)	(.008)	(.007)
Election Year Dummy	.008	$.027^{\circ}$	-.00002	$-.018^{\circ}$
	(.015)	(.014)	(.012)	(.010)
Buyer Number of Contracts (log)	$.077^{***}$	$.063^{***}$	$.060^{***}$	$.052^{***}$
	(.008)	(.009)	(.007)	(.007)
Buyer Contract Value (log)	$.010^{*}$	.005	$.018^{***}$	$.021^{***}$
	(.004)	(.006)	(.004)	(.004)
CRI, Election Year Interaction	.008	.024	.004	-.002
	(.015)	(.016)	(.017)	(.015)
Constant	$-.138^{*}$		$-.141^{*}$	
	(.065)		(.057)	
Model	Pooled OLS	Buyer FE	Pooled OLS	Buyer FE
Type, Location, Sector+ Dummies	Yes	-	Yes	-
Observations	1,806	1,806	1,491	1,491
R^2	.279	.079	.249	.102
F Statistic	22.924^{***} (df = 30; 1775)	16.340^{***} (df = 5; 948)	27.157^{***} (df = 18; 1472)	23.362^{***} (df = 5; 1030)
Note:				+Sector only available for Hungary °p<.1; *p<.05; **p<.01;***p<.001

Appendix B – Permutation tests of the regression results

In order to address concerns of non-independence of observations in the network, we permute the dependent variable (competitive clustering) and rerun the two fixed-effects regressions in Table 5, 1000 times. We count the number of times the observed coefficient on CRI is less than the randomized coefficient and generate a p-value. We plot the two distributions, for Hungary and Czech Republic, below. Results are the same as in the regressions reported in the main text.

FIGURE B1: DISTRIBUTIONS OF 1000 CRI COEFFICIENTS FROM FIXED-EFFECT REGRESSIONS WITH RANDOMIZED DEPENDENT VARIABLE (COMPETITIVE CLUSTERING). OBSERVED COEFFICIENTS MARKED IN RED.



Appendix C – Regressions with year dummies

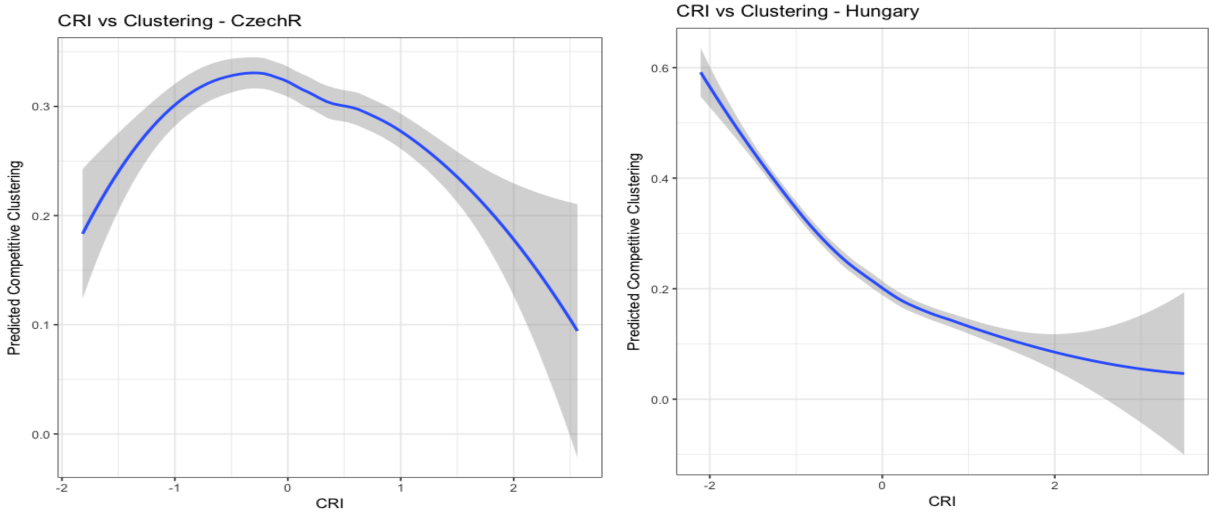
As an alternative model specification, we substitute year fixed effects for the election year dummy in the models in Table 5. We note that the coefficient on CRI in the Czech Republic is no longer significant. We investigate this in more detail below.

TABLE C1: POOLED OLS AND BUYER, YEAR FIXED EFFECTS MODELS PREDICTING BUYER COMPETITIVE CLUSTERING IN HUNGARY AND CZECH REPUBLIC.

	Dependent Variable: Buyer Competitive Clustering, >=5 Contracts			
	Hungary		Czech Republic	
	(1)	(2)	(3)	(4)
CRI	-.073***	-.049***	-.017**	-.005
	(.005)	(.005)	(.006)	(.006)
Buyer Number of Contracts (log)	.139***	.106***	.156***	.128***
	(.006)	(.007)	(.006)	(.006)
Buyer Contract Value (log)	-.016***	.002	.004	.010**
	(.003)	(.004)	(.003)	(.004)
Constant	.027		-.133**	
	(.050)		(.047)	
Model	Pooled OLS	Buyer, Year FE	Pooled OLS	Buyer, Year FE
Type, Location, Sector+ Dummies	Yes	-	Yes	-
Observations	3,657	3,657	2,704	2,704
R^2	.436	.199	.466	.335
F Statistic	84.938*** (df = 33; 3623)	57.049*** (df = 8; 1835)	97.489*** (df = 24; 2679)	90.876*** (df = 10; 1808)
Note:				+Sector only available for Hungary °p<.1; *p<.05; **p<.01;***p<.001

As in Figure 8 we plot the LOESS smoothed model prediction for competitive closure as a function of CRI for the fixed-effects models in Table C1.

FIGURE C1: MODEL VISUALIZATIONS, CZECH AND HUNGARIAN CRI VS COMPETITIVE CLOSURE.



Given the suggested inverse quadratic relationship between CRI and competitive clustering in the Czech Republic, we rerun the models with a quadratic term for CRI. We argue that our substantive findings are preserved: in the above average CRI regime, there is a clear negative relationship between CRI and competitive closure, especially at the upper half of the CRI distribution where complete capture is more likely to be present.

TABLE C2: POOLED OLS AND BUYER, YEAR FIXED-EFFECTS MODELS PREDICTING COMPETITIVE CLOSURE, INCLUDING A QUADRATIC TERM FOR CRI.

	Dependent Variable: Buyer Competitive Clustering, >=5 Contracts			
	Hungary		Czech Republic	
	(1)	(2)	(3)	(4)
CRI	-.073***	-.049***	-.010	.004
	(.005)	(.005)	(.006)	(.007)
CRI Squared	.019***	-.004	-.018***	-.017**
	(.004)	(.004)	(.005)	(.005)
Buyer Number of Contracts (log)	.137***	.106***	.156***	.129***
	(.006)	(.007)	(.006)	(.006)
Buyer Contract Value (log)	-.012***	.002	.003	.009*
	(.003)	(.004)	(.003)	(.004)
Constant	-.028		-.098*	
	(.050)		(.049)	
Model	Pooled OLS	Buyer, Year FE	Pooled OLS	Buyer, Year FE
Type, Location, Sector+ Dummies	Yes	-	Yes	-
Observations	3,657	3,657	2,704	2,704
R^2	.441	.200	.469	.338
F Statistic	84.012*** (df = 34; 3622)	50.810*** (df = 9; 1834)	94.699*** (df = 25; 2678)	83.822*** (df = 11; 1807)

Note: +Sector only available for Hungary
°p<.1; *p<.05; **p<.01;***p<.001

Appendix D – Yearly persistence graphs

Below we plot the distributions of persistences among captured and non-captured buyers for both countries across all years. When the intervening year saw a change in the central government (2010 for both countries), we shade the period yellow.

FIGURE D1: PERSISTENCE OF CAPTURED AND NON-CAPTURED YELLOW. HUNGARIAN BUYER PERSISTENCE. PERSISTENCE ACROSS YEARS WITH CHANGE OF GOVERNMENT SHADED YELLOW.

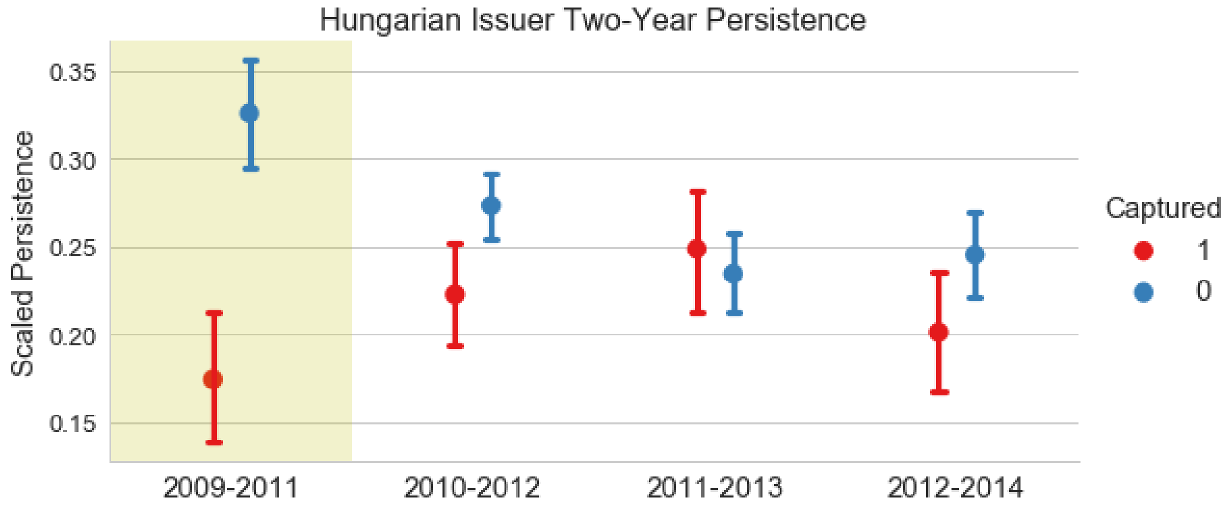
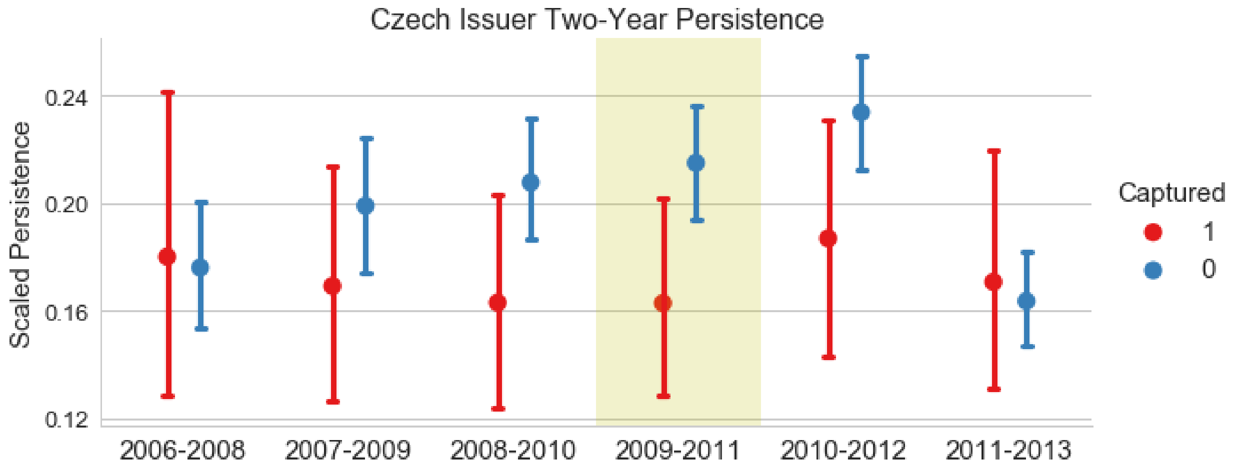
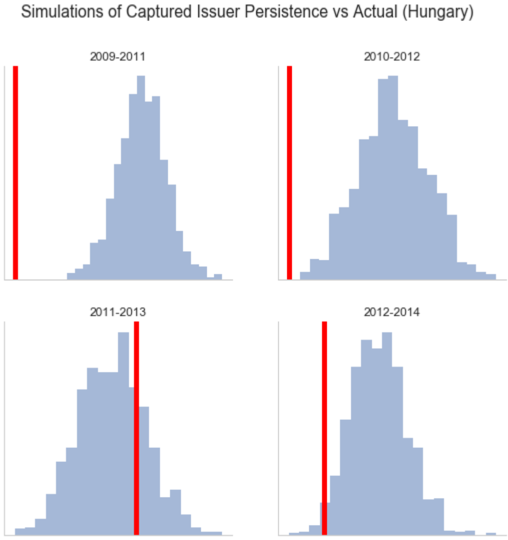


FIGURE D2: PERSISTENCE OF CAPTURED AND NON-CAPTURED YELLOW. CZECH BUYER PERSISTENCE. PERSISTENCE ACROSS YEARS WITH CHANGE OF GOVERNMENT SHADED YELLOW.



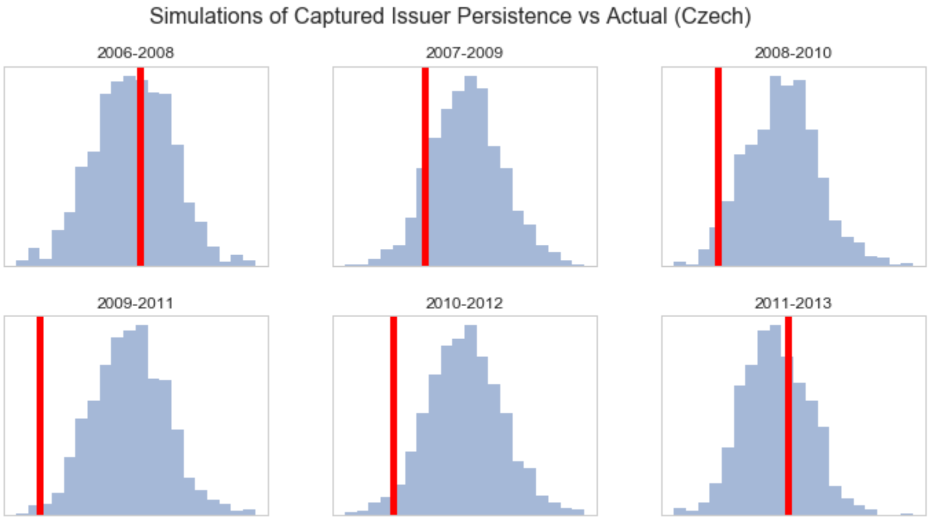
Appendix E: Histograms of Capture Persistence Randomized vs Actual

FIGURE E1: THE DISTRIBUTION OF 1000 INSTANCES OF HUNGARIAN CAPTURED ISSUER PERSISTENCE WITH THE CAPTURED LABEL RANDOMLY PERMUTED



Note: The red line indicates the true value of captured issuer persistence.

FIGURE E2: THE DISTRIBUTION OF 1000 INSTANCES OF CZECH CAPTURED ISSUER PERSISTENCE WITH THE CAPTURED LABEL RANDOMLY PERMUTED



Note: The red line indicates the true value of captured issuer persistence.